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Towards robust renewable energy investment decisions at the territorial level

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HIGHLIGHTS

- Profound future uncertainty is present when planning renewable energy investments.
- Many decisions are made at the territorial level, especially related to heating.
- Simple decision-making tool allowing consideration of uncertainties is needed.
- We seek robust solutions performing well over a wide range of plausible futures.
- Current domestic natural gas heating performs badly in all futures simulated.

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ABSTRACT

Considerable and fast investments in renewable energy technologies are needed in order to reduce greenhouse gas emissions to achieve the Paris Agreement climate change mitigation targets. Many of these investment decisions are made at the territorial level, especially those related to the heating sector. When choosing the most suitable energy investments, decision makers need to consider several performance indicators—economic, social and environmental—simultaneously. In addition, decision makers face profound uncertainty concerning the future, as decisions on energy systems are always long-term investments. We aim to provide territorial decision makers with a simple decision-making framework that combines a robust decision-making method with multi-criteria analysis and allows the inclusion of territorial features. The main aim is to develope a simple tool that provides data to seek robust solutions which will perform well over a wide range of plausible futures. The method proposed is illustrated with a case study on renewable heating solutions based in France. Heat pumps or central biomass plants are robust in various future conditions, while current domestic natural gas based heating performs badly compared to the renewable technologies.

1. Introduction

Considerable investments in renewable energy technologies are needed in order to reduce greenhouse gas (GHG) emissions to achieve the Paris Agreement climate change mitigation target to limit global warming below 2 °C [1,2]. Many of these investment decisions are made at territorial level and the local decision makers such as the local administrators, municipal planners and local industries play a role in the decision-making process.

When selecting the most suitable renewable energy options for a territory, local decision makers face multiple questions. These questions are related to the technical properties and costs of renewable energy technologies, the resources available in the region (e.g. biomass, solar radiation, geothermal and excess energy sources), as well as the existing local energy system and industrial activities. The decision makers need to consider several viewpoints—economic, social, and environmental—simultaneously, to choose the most suitable energy solutions for the region. Thus, decision makers face a decision-making problem in which multiple criteria need to be considered simultaneously. They also face the profound uncertainty of the future, as decisions on energy systems are always long-term investments (e.g. 20–50 years lifetime), the development of novel technologies may be faster or slower than anticipated, the prices of various fuels and feedstock can vary significantly, and the global climate and energy policy developments can affect

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the profitability or the expected impacts of certain technologies. Significant uncertainty related to the energy system studies is widely acknowledged, but only a minor part of the studies uses uncertainty analysis methods [3].

Several methods have been developed for decision making under uncertainty, and presented e.g. by Marchau et al. [4]. In addition, numerous tools are available for multi-criteria decision making [5]. An important question is what kinds of results and data are useful for the decision makers when they select between investment options? Another question is the level of complexity of the tools used, in terms of the research resources available as well as the ability to interpret and apply the results. This is especially relevant at the territorial level, where the resources for complex studies may be limited.

In this study, we aim to build an easily approachable decision making framework, yet with a strong focus on uncertainties. We focus on the robust decision-making method [6] and aim to combine it with features of multi-criteria analysis. The core of the approach is that we want to improve the decision maker's understanding of the conditions that make a technology succeed or fail, and the possible trade-offs. We aim to provide territorial decision makers with a robust and flexible tool, which can adapt to different levels of data available and different level of detail in the models and evaluation methods used. By territory, we mean an area smaller than the national scale (e.g. a county, district, municipalities, department, or commune) with some kind of internal coherence regarding the environment, actors, or governance. While several definitions have been proposed for 'territory' [7–9], the final definition should be case specific.

We test the method proposed by studying renewable heating investments. The territorial context is especially suitable for heating systems, as they are mostly local solutions. For example, in contrast to electricity, heating systems do not have international transfer grids. In addition, heating is a timely topic as the sector is facing a huge transition process [10]. Currently, around half of the energy consumption in the EU is due to heating and cooling in buildings and industry [11]. According to the Commission's impact assessment for 2030, the heating sector is one of the core sectors where emission reductions are needed, and at least 40% of heating should be produced by renewables by 2030 [10]. In 2018, only 21% of the total energy used for heating and cooling in the EU was produced by renewable energy [12]. Here we present an illustrative case study in the Isére department in France for selecting the most robust renewable heating options.

The article consist of the following sections: First, we present a short review of the robust decision-making and multi-criteria analysis methods, how they deal with uncertainties, their benefits and challenges, and which of their features we aim to include in the decision-making framework proposed. Then we present the method proposed and illustrate the assumptions for the case study. This is followed by the results and discussion. Finally, we provide conclusions and further needs for development.

2. Literature check

In their book Marchau et al. 2019 [4] present various methods for decision making under deep uncertainty (DMDU), including Robust Decision Making (RDM), Dynamic Adaptive Planning (DAP), Info-Gap Decision Theory (IG) and Engineering Options Analysis (EOA). RDM and IG search for robust policy solutions, while DAP emphasizes the importance of monitoring and adaptation to changes over time to prevent a chosen policy from failure. An EOA presents a more detailed analysis of technical alternatives, and can complement the other approaches [4].

In our study, we concentrated on the RDM method, as it provides one answer to the question of what kinds of results and data are useful for the decision makers when they select between policy and investment options. We have constantly increasing computational power to create models to provide responses to our questions [13]. However, already almost 30 years ago Bankes [13] noted that the increased use of models does not always improve the quality of decision-making, but rather increases the discussion on sensitivities and shortcomings related to the models themselves. He proposed that we should focus on "explorative modelling" and include the future uncertainty as an inherent part of the analysis. With explorative modelling, he meant using models for series of computational experiments in the uncertain future. Bankes's idea is behind the development of a method known as "scenario discovery" or "robust decision-making" by Lempert et al. [14], Groves and Lempert [15] and Bryant and Lempert [16].

In RDM, we model a large number of possible futures and test our technological solution in all these futures. The aim is to find the future conditions which make the solution or scenario studied fail or succeed [16,17]. This helps the decision maker choose strategies that are more robust and can more effectively achieve their goals in an uncertain future [16]. The idea is to seek robust, rather than optimal strategies, which perform well over a wide range of plausible futures [6]. The RDM method has been applied e.g. by Kasprzyk et al. [18] to study a city's water supply, by Forsström [17] and Perrier [19] to study future energy systems, and by Björnberg [20] to study fossil-free industrial systems. Moallemi applied parts of the method (PRIM analysis) to study the transition of an electricity system [21]. In addition, the method has often been applied to complex systems, e.g. on adaptation to climate change [22]. Lindroos et al. [23] have applied parts of the method to study the role of bioenergy combined with carbon capture and storage in a district heating and cooling grid, but otherwise the authors are not aware of RDM studies specific on heating sector.

The benefit of the RDM and other DMDU approaches is that they concentrate on finding solutions that can adapt to various future circumstances. This sets them apart from more traditional "predict then act" strategies for long-term decision-making [4], and they can rather be considered as "assess-risk-of-policy" approaches [22]. Kwakkel and Haasnoot [24] point out that in the literature there is "an emerging consensus that any decision regarding a complex system should be robust with respect to the various uncertainties". They further state that under deep uncertainty, decision-making support should move away from trying to define one correct solution, and rather aim at enabling discussion and common understanding between the stakeholders. Popper et al. [25] state that simple exploratory modelling, such as RDM can be seen as a tool for an initial check to identify the most important factors affecting the decision-making. These factors can then be further investigated with additional methods or models.

Marchau et al. [4] report also on the challenges of DMDU approaches. The models and tools used should be developed so that they are simple and transparent enough, and more guidance is needed on when and how to apply DMDU tools. In addition, the scope of the application of DMDU tools could be broadened, and suitable sectors could for example include transportation, energy and spatial planning [4]. In this article, we provide a user case for the heating sector.

In addition to the problem of uncertainty, decision makers often face a situation where several indicators need to be considered simultaneously. Numerous methods of multi-criteria decision making (MCDM) are available and widely applied also for renewable energy technologies [5]. The MCDM methods are generally divided under two groups: Multi-Attribute Decision Making (MADM) and Multi-Objective Decision Making (MODM) [26]. The MADM methods are applied when the problem has a small and finite set of solutions, and it aims at identifying the best option based on the known attributes of a limited number of alternatives. MCDM methods applied for this type of problems include e. g. AHP, ANP, TOPSIS, DEMATEL, ELECTRE, PROMETHEE, and UTA [26]. The MODM methods are applied when there is a large and infinite set of alternative solutions. Several objectives are simultaneously taken into account within a mathematical programming model, and the aim is to find the best solution that satisfies the decision maker's desires. The results can be presented e.g. as Pareto-efficient solutions. The methods include e.g. Ɛ-constrain, Global Programming, and the Weighting method [26].

Uncertainty in an MCDM analysis can be handled by various means. Stewart and Durbach [27] have classified uncertainty as internal and external uncertainty. With internal uncertainty they mean the uncertainty of the MCDM model itself, as well as the human judgement of the criteria. With external uncertainty they mean the lack of knowledge about the consequences of a particular choice, which relates to the main interest of this paper in profound future uncertainty. Stewart and Durbach [27] conclude that there is always a role for systematic sensitivity analysis "but care needs to be taken to avoid simple one-at-a-time variations in assumptions". Sophisticated approaches are used for uncertainty in MCDA, such as fuzzy set approaches. Fuzzy set approaches have been widely proposed for energy policy planning [28], and they allow the expression of uncertainties in human opinions through the concept of partial truth, in which the truth-value may range between completely true and completely false. Stewart and Durbach [27] also see the benefit of combining MCDA with scenario planning, as this can be a very transparent tool to illustrate uncertainties to decision makers. However, an open question is what a suitable number of the scenarios is. Here RDM could provide one solution with its approach to simulate a large variety of futures possible. Stewart and Durbach [27] also conclude that it is important that the analyses are fully understandable to all participants in the process, and thus very elegant mathematical models may be of less practical value, especially in the cases where fewer research resources are available. The comprehensibility of the method to the users is one of our main aims.

Luca et al. 2017 [29] and Gamper and Turcanu 2007 [30] have listed benefits and challenges of MCDM. The benefits include the comprehensiveness of the analysis, the learning process for the participants, a common understanding of the problem, the systemic transparent process, and a clearer view of sustainable solutions. On the other hand, the challenges of the analysis can include the fact that the analysis brings more uncertainties and methodological disagreements, that it is technically complex and difficult to understand, simplifies the decision context and is time consuming. Wu et al. 2017 [31] concluded that different MCDA methods provide different results even to the same problem and with the same data, and it is usually difficult to determine which method provides the most appropriate solution. They propose that a reasonable solution would be to apply a combination of two or more MCDA methods. At the same time, Mardani et al 2017 [5] highlighted that the MDCM approach should be easily understood. If the decision makers cannot understand how a methodology works, they may see it similarly to black box and loose trust in the method. This adds to the reasons why we aim for a simple method which can be used as an initial check of the problem in hand.

For building a simple decision making-framework for territories, we compared example studies with multi-criteria and RDM methods to show the benefits and differences (Table 1).

We aim to combine some characteristics and benefits of the methods presented above into a simple decision-making framework with the following properties:

– inclusion of uncertainty as an inherent part of the analysis,
– creating common understanding for the stakeholders on the future vulnerabilities and trade-offs,
– inclusion of multiple indicators,
– inclusion of territorial features to the analysis as weighting factors.

The need for this kind of hybrid approaches has been identified also by e.g. Sharma et al. [35], who have combined energy systems optimization models with multi-criteria assessment and stakeholder participation via workshop. Our main aim is to provide decision makers with a simple tool providing data that allows seeking robust solutions which perform well over a wide range of plausible futures.

3. Proposed decision-making framework

The decision-making framework proposed is illustrated in Fig. 1. This section describes the principles of the analysis. Section 4 with the case study illustrates how the analysis is done in practice. The analysis is participatory and can be conducted in co-operation with the decision makers, as illustrated in Fig. 1. It can be used for both analysing individual technologies or technology portfolios.

The analysis is based on the territorial data and characteristics, which define the local technical, social, and environmental conditions. This data provides the basis for the choice of suitable technologies to be included in the study. For example, the local energy consumption and current production; local feedstock, solar radiation, and wind conditions; possible excess heat and geothermal sources; as well as heat storage possibilities all affect which renewable energy technologies or their combinations are suitable for the region. In addition, the social features such as the density of habitation, or environmental features such as vulnerable landscapes can affect the choice. This "structural" information providing a first diagnosis of the territory are possible preconditions for engaging in the decision-making process. The framework can be used with different levels of data available in the territory. Whatever the in-depth quality of the data used, the proposed methodology provides information at the strategic level and not the operational one.

Table 1
Comparison of MCDM methods and RDM.

Study	Multi-criteria analysis with ranking Example: [32]	Search for Pareto optimal solutions Example: [33,34]	Robust decision-making Example: [16,17]
Method	• Multi-criteria analysis and weighting by preference scenarios	• Optimisation or simulation model to find Pareto optimal solutions or to illustrate Pareto front	• Robust decision-making by means of regret analysis and PRIM statistical analysis
Decision maker's role (with analyst)	• Selects the technologies studied • Selects the criteria used • Can select the weighting preferred	• Selects the scenarios studied • Selects the criteria used	• Selects the technologies/scenarios studied • Selects the performance metrics used • Defines future uncertainties for parameters (no need for agreement)
Results	• Show final total score or weighted score for each studied system • Show the ranking of the systems	• Pareto frontier • Show the trade-offs between different indicators	• Show which future assumptions make the scenario succeed or fail (and which parameters are less important)
Decision based on	• The DM chooses the winning system based on final ranking and his judgement on the weighting values	• The DM chooses the optimal strategies based on a judgement on the trade-offs between the various criteria	• The DM chooses the most robust (or other) scenario based on the information on the scenario's performance in different futures, and on a judgement on how probable this future is
Benefits	• Simplicity, easy to understand • Multiple criteria possible • Weighting provides a way to illustrate various preferences	• Illustrates the trade-offs between criteria	• No need for agreement on assumptions of uncertainty • Inclusion of uncertainties is an inherent part of analysis • Illustrates which assumptions are the most relevant in uncertain future and what are their trade-offs

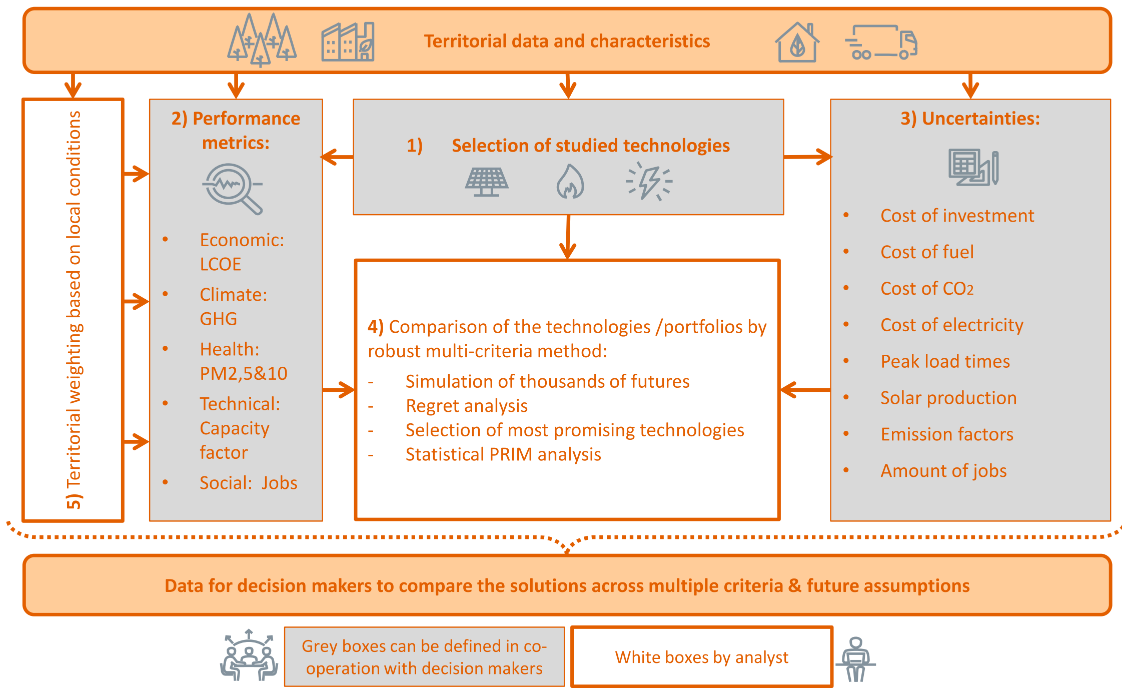

Fig. 1. Illustration of the proposed decision-making framework with examples for performance metrics and uncertain factors. The box numbers illustrate the order of the process.

3.1. *Robust decision making method with multiple performance metrics*

The Robust Decision-Making method was developed by the RAND corporation [14,15] and has been described by Bryant and Lempert [16], and applied e.g. by Forsström [17] and Perrier [19]. The method aims to test a proposed solution (e.g. technology or portfolio of technologies) in thousands of different futures to determine whether the solution is robust in different future conditions.

The methodology is based on defining the following factors [14,17]:

- *Uncertain factors (U)* describe the factors outside the control of the decision makers. These factors can however be fundamental in defining the success of a technology/strategy in the future. These are factors such as investment costs, prices of fuel or feedstock in the future, the price of CO_2, or other uncertain emission parameters. An uncertainty range is defined for all these parameters. The uncertainties can be defined in co-operation with the decision makers, and there is no need for agreement on the values, as wide uncertainties can be included. For example, if one decision maker thinks that in the future the price of CO_2 will be 150 €/t and another one believes that it will be 10 €/t, both opinions can be included, and the variation is fixed between 10 and 150 €/t. A uniform distribution is used as all the values are considered equally probable. During the analysis some iteration can be carried out and the uncertainty range can be reduced or widened in accordance with the decision maker choices.
- *Factors under control* (C) comprise actions that are in the decision maker's hands. These can be for example: the selection of technologies that the decision maker wants to study, some of the technical characteristics, and some parameter restrictions.
- *Models (M)* include the models used in the study, which can be simulations of optimisation models. The requirement is that the model is simple enough so that it can be used to study thousands of futures.
- *Performance metrics (P)* are the metrics used to rank the technologies or portfolios (e.g. economic, environmental, and social metrics). These can be selected by the decision makers. The performance metrics correspond to the various criteria used in multi-criteria analysis.

The analysis of the success of a solution is based on a regret analysis [17]. This means that we study the success of each technology in each of the simulated futures (e.g. 5 000 futures, meaning 5 000 different combinations of the calculation parameters). This is done by comparing the performance of a technology to the performance of other technologies in the same future. The regret is 0 for the technology which performs the best in that particular future (e.g. the technology which has the lowest costs or lowest emissions). The regret (R) is calculated for each future and for each performance metric by:

When the minimisation of a performance metric is preferred (e.g. cost or emission)

$$R_{pm}(j,f) = C_{pm}(j,f) - min_j\{C_{pm}(j,f)\}, \tag{1}$$

When the maximisation of a performance metric is preferred (e.g. amount of jobs created)

$$R_{pm}(j,f) = max_j\{C_{pm}(j,f)\} - C_{pm}(j,f), \tag{2}$$

where

R = regret,
C = is the performance index of the performance metric in question (e.g. €/MWh or gCO_2/MJ),
pm = performance metric
j = strategy (e.g. technology or portfolio),
f = future.

In order to normalise the results between the different performance metrics, the regret results are used to calculate the "points" (x) for each technology and each performance metric. The point varies between 0 and 1, being 1 for the best technology. The normalisation is done by studying the distance of the particular regret result from the maximum regret in the same future:

$$x_{pm,jf} = \frac{max_j\{R_{pm}(j,f)\} - R_{pm}(j,f)}{max_j\{R_{pm}(j,f)\} - min_j\{R_{pm}(j,f)\}}. \quad (3)$$

The final "total points" (X_{tot}) is the sum of the final average points of all the studied performance metrics for the technology.

$$X_{tot} = \sum x_{pm,ave,i}. \quad (4)$$

3.2. Vulnerable future discovery

One internal part of the robust decision-making method is so called vulnerable future discovery. It is applied to identify the uncertain inputs that best predict the future conditions when the technologies or strategies studied become vulnerable (or alternatively where they perform well). For example, we can search for combinations of parameters which cause the worst 10% of the results for a technology. Finally, we want to illustrate these futures of vulnerability (or success) to the decision makers so that they can decide if they believe those conditions would take place or not. For example, the analysis could show that with a certain combination of CO_2 and fuel prices, a technology would most probably fail, and the decision maker can then judge if he sees these prices to represent the future he believes will take place or not.

The method for the vulnerable future discovery is described in Bryant and Lempert [16] and in Kasprzyk et al. [18]. The analysis uses the Patient Rule Induction Method (PRIM) by Friedman and Fisher [36], and it can be applied by using the R programming language [37] and SDToolkit [38]. A tool for Python programming is also available [see 19]. In the discovery process, we first define the performance thresholds for the regret analysis and then find the drivers for the threshold violations (the combinations of parameters causing the vulnerable futures). With the cases passing the performance threshold defined, the PRIM creates "scenario boxes" which describe the values causing violations of the threshold (Fig. 2).

The PRIM method is interactive and by visualising the results, it helps the user to choose the best scenario boxes and balance them with the three measures of scenario quality: the coverage, density, and interpretability of the scenario box. The coverage quantifies how many of the vulnerable points are captured in the scenario, whereas the density shows how many of the captured points are actually in the vulnerable set [17]. The user wants to maximise both the coverage and the density of the scenario box.

3.3. Portfolio construction

Often one technology is not enough to supply the whole need for renewable energy in a territory, but rather a portfolio of technologies is needed. In addition, the impact of a technology portfolio can be different than the impact of an individual technology [39]. Thus, technology portfolio evaluation with the methodology proposed is also illustrated in this paper. To construct a technology portfolio we need information on the energy demands in the territory, which is then fulfilled with a combination of technologies. The portfolio construction in our case study is further explained in Section 4.4.

3.4. Preference scenarios and territorial weighting

In a multi-criteria analysis, the weighting of the various criteria is often applied. Klein and Whalley [32] and Nock and Baker [39] have applied a weighting of multiple criteria with "preference scenarios" describing the decision maker's preferences. For example, one can consider the economic criteria to be more important than the climate criteria, or the other way round, and give weights to the points accordingly. The weighting is often somewhat subjective, and one could argue that the weights can be modified until the results present the initial opinion of the decision maker. However, for example Klein and Whalley [32] show the ranking of the technologies over several decision preference scenarios which allows the decision maker to make a robust choice of a technology, which performs well with different kinds of weighting scenarios, i.e. ranks highest on average.

The weighting "preference scenarios" could also be based on territorial features. In life cycle assessment (LCA) studies this kind of "spatialization" has already taken place. For example Nitschelm [9] and Patouillard [40,41] have studied the spatialization of LCA and the use of spatialized characterisation or sensitivity factors in impact assessments. This means that when studying the environmental impacts, the local environmental characteristics such as soil quality, slope, watershed conditions, distance to water, etc. are included in the analysis. The spatial resolution naturally varies for different impact categories (e.g., GHG impacts are global, while soil quality impacts are specific to a land area). A similar idea of "sensitivity factors" could be applied for the preference weighting factors in territorial, multi-criteria analyses, based on regional circumstances. A simple example could be that in a region which is poor, isolated, and has high biodiversity values, the weighting of the criteria could illustrate these features. For example, a high weight could be set for economic indicators to emphasise low-cost technologies, a low weight could be set for health indicators as particulate emissions are not so harmful in isolated areas, and a high weight could be set for biodiversity to select technologies with low biodiversity impacts. Some propositions for the "spatialization" of weighting indicators are listed in Table 2. These indicators can be seen as a structural, territorial initial check that could be used during the analytical process to help the decision makers.

4. Case study

We illustrate the use of the method presented in Section 3 in a case

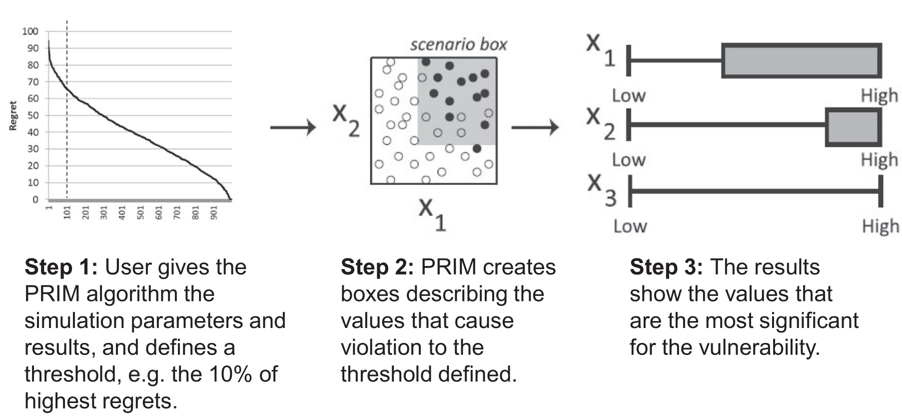

Fig. 2. Principle of the PRIM analysis (Figure adapted from Kasprzyk et al. 2013).

Table 2
Possible indicators for regional weighting.

Criteria	Performance metric	High weight given to criteria if	Low weight given to criteria if	Possible indicator
Economic	LCOE	The region is poor	The region is rich	€/person (e.g. BIP in the region per inhabitant)
Climate	GHG emissions	The region is rich There are ambitious regional targets to reduce GHG emissions	The region is poor	€/person (e.g. BIP in the region per inhabitant) % of emissions reduction in regional climate strategy
Health	PM10/PM2.5	Densely populated	Isolated	Persons/m^2
Social	Jobs	There is a high unemployment rate	There is a low unemployment rate	Unemployment%
Technical	Capacity factor	There is a high proportion of wind and solar in the energy system	There is a low proportion of wind and solar in the energy system	Share of wind and solar in the regional energy system
Environ mental	Biodiversity	There are important areas for biodiversity in the region	There are less important areas for biodiversity in the region	Protected areas/ecosystems, Natura areas, etc. in the region (m^2/m^2)
Water	Acidification/ Eutrophication Water footprint	There are important/vulnerable watersheds in the region The region is vulnerable to droughts	There are no watersheds in the region The region is not vulnerable to droughts	Protected watersheds/distance to water/state of watersheds in the region Meteorological data on droughts

Table 3
Technology selection and key parameters.

Identification	Technology	Output capacity	Input	Example capacity MW	Conversion efficiency GJ/GJ	Panels installed m^2	Life time y	O&M costs % of investment
Technology 1	2 MW, forest biomass	Heat (2 MWth)	Forest residues	2	0.85		25	4%
Technology 2	20 MW, forest biomass	Heat (20 MWth)	Forest residues	20	0.85		25	4%
Technology 3	Central heating biomass	Heat (0.15MWth)	Forest residues	0.15	0.85		20	4%
Technology 4	Domestic biomass, traditional	Heat (0.010 MWth)	Wood logs	0.01	0.75		15	6%
Technology 5	Domestic biomass, modern	Heat (0.010 MWth)	Pellets	0.01	0.90		15	6%
Technology 6	Domestic solar heating	Heat (0.0035 MWth)	Solar radiation	0.0035		5	20	2%
Technology 7	Central solar heating	Heat (0.15 MWth)	Solar radiation	0.15		214	25	2%
Technology 8	Domestic heat pumps	Heat (0.010 MWth)	Electricity	0.01			15	3%
Technology 9	Central heat pumps	Heat (0.10 MWth)	Electricity	0.15			20	3%
Technology 10	2 MW, natural gas	Heat (2 MWth)	Natural gas	2	0.9		20	2%
Technology 11	Domestic natural gas	Heat (0.015 MWth)	Natural gas	0.01	0.9		20	6%

study considering a medium-sized community in the Isère region in France (based on the characteristics of the Fontaine community of around 22 000 habitats). The study follows the framework presented in Fig. 1.

4.1. Technology selection

The heating technologies studied and their main characteristics are listed in Table 3. The data on technologies is from European and French studies [42–44]. The large biomass heat plants as well as all the central solutions (central heat pumps and solar heating) are assumed to be attached to a district-heating system. Therefore, the costs of construction of the distribution network are also considered for these technologies. Natural gas heating is included as a fossil reference, representing the current practice.

4.2. Definitions for robust decision-making

The definitions (see Section 3.1) used for the robust decision-making analysis are listed in Table 4. The parameters within control include the conversion efficiencies and lifetimes of the technologies, which were fixed in the study. The uncertain factors include all the data related to

Table 4
The definitions needed for robust decision-making for the case study.

Within control (C):	**Uncertain factors (U):**
• Technology selection • Conversion efficiencies • Portfolio construction	• Cost of investment • Cost of biomass • Cost of natural gas • Cost of CO_2 • Cost of electricity • Peak load times • Solar production • GHG emissions • PM emissions • Number of jobs
Models (M):	**Performance metrics (P):**
• Excel-based model to analyse the technologies, 5 000 futures simulated • Excel-based model to construct the portfolios, 5 000 futures simulated	• Economic: LCOE • Climate: GHG • Health: $PM_{2.5}$ and PM_{10} • Technical: capacity factor (used only for the comparison of individual technologies) • Social: Jobs

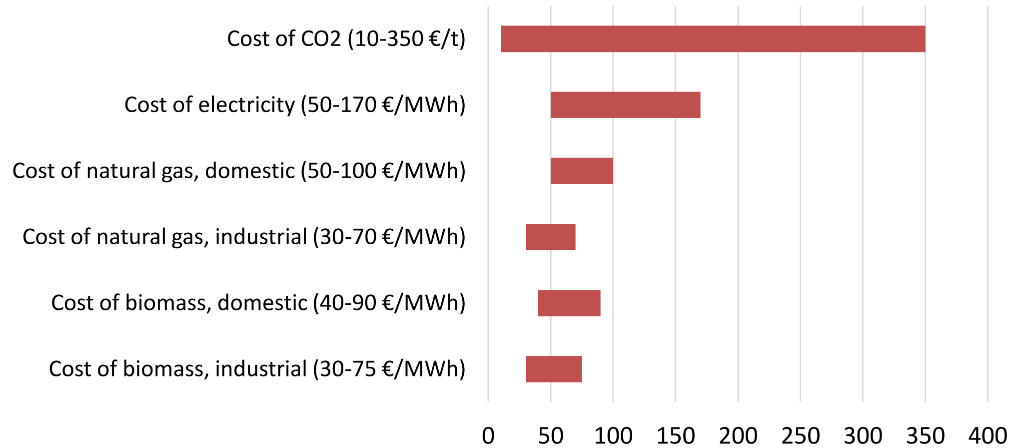

Fig. 3. The variation of costs in the robust decision-making analysis based on expert opinion.

the costs of the technologies, fuels used, and the price given for CO_2. Here the CO_2 price was applied for fossil fuels, even in domestic use. In addition, the emission indicators were considered as somewhat uncertain, as the biomass used in the plants could come from different biomass sources and over different distances, and as there is always some degree of uncertainty related to LCA results.

The model used in this study is built in Excel and allows the simulation of 5 000 future cases. The 5 000 futures were created by combinations of 5 000 random values of the calculation parameters within their uncertainty ranges (Section 4.3). An Excel-based model was used also for the portfolio definition. In further analyses, these models could be replaced with more refined tools.

The performance metrics selected for the case study illustrate the economic performance for the levelized cost of energy (LCOE), climate impacts by GHG emissions, health impacts by particulate emissions ($PM_{2.5}$ and PM_{10}), technical properties by capacity factor (CF), and social impacts from the jobs created. The indicators are limited to 5 to simplify the analysis, but more performance metrics such as biodiversity impacts, water consumption, or more refined social indicators could also be added to the analysis.

The LCOE results were calculated by the equation presented below [43].

$$LCOE = \frac{\sum_{t=1}^{n} \frac{I_t + M_t + F_t}{(1+r)^t}}{\sum_{t=1}^{n} \frac{E_t}{(1+r)^t}} \tag{5}$$

where

I_t = investment expenditures in the year t,
M_t = operation and maintenance expenditures in the year t,
F_t = fuel expenditures in the year t,
E_t = energy generation in the year t,
r = discount rate (discount rate of 5% was used here),
n = lifetime of the system.

The performance metrics are evaluated in terms of varied and fixed costs or emissions (e.g. €/MWh and €/MW or gCO_2/kWh and gCO_2/kW), as demonstrated by Nock and Baker [39]. For the portfolios, the final performance of the portfolio is the sum of the performance of the different technologies in the portfolio. This sum is calculated by weighting the varied costs/emissions by the share of the technology in portfolio in terms of MWh, and by weighting the fixed costs/emissions by the share of the technology in portfolio in terms of MW. The jobs created are only evaluated in terms of jobs per MWh due to the data available. For the technology comparison, the capacity factor was varied to illustrate the potential peak load hours for each technology. The capacity factor indicator is not included in the portfolio metrics, as it is already fixed in the portfolio construction.

The performance metrics could also be evaluated locally and globally. For example, the fixed GHG emissions related e.g. to the manufacture of solar panels are not produced locally, whereas the particulate emissions of biomass combustion are local. Here we consider the global emissions as the total impacts of the technologies of interest.

4.3. Setting the uncertainties for the parameters

Setting the uncertainties for the calculation parameters can be done in co-operation with the specialists and decision makers. Especially, estimations related to the future costs of technology investments, fuel and CO_2 prices can vary significantly, depending on who is asked. The robust decision-making process allows all the opinions to be included, as wide uncertainty ranges can be applied. Here the uncertainty ranges are based on the literature and on expert opinions.

The CEA experts evaluated the possible variation in the cost of fuels and CO_2 in France (Fig. 3). The CO_2 price was assumed to have a wide uncertainty range, as it has been estimated that in France, the shadow prices of carbon[1] could be close to 800€ in 2050 [45]. The electricity price was estimated not to fall below 50€/MWh, as an important share of the price is formed by distribution costs. The industrial use of natural gas or biomass was estimated to be lower in cost than domestic use. The investment costs were based on ADEME [43] and Sandvall [46].

The COP for heat pumps stands for 'coefficient of performance' and shows the ratio of useful heating or cooling provided for work required, i.e. the electricity consumed by the pump. The higher the COP, the more efficient the heat pump (Fig. 4).

Here the typical timeframe for defining the cost estimations is around 20 years. However, as the method allows a large variation of the parameters, it is possible to include a range that presents the possible price development on any wanted time scale.

The GHG emissions for bioenergy options were taken from the EU Renewable Energy Directive 2 [47], where the default emission factors are given for various types of biofuels. The Ecoinvent database was used to estimate the rest of the GHG emissions, as well as particulate emissions [48]. The capacity factors were evaluated based on S2Biom [42], ADEME (2016) and Klein & Whalley [32]. Data on jobs was based on the ADEME study on the jobs created by various renewable energy technologies in France [49], and the study by Klein & Whalley [32]. These

[1] A generic definition can be found in Drèze and Stern (1990) [54]: "The shadow prices are the social opportunity costs of the resources used (and correspondingly for outputs generated)". In Quinet (2019), the shadow price is the value of an avoided CO_2 tonne through a mechanism including CO_2 externalities into public economic computations.

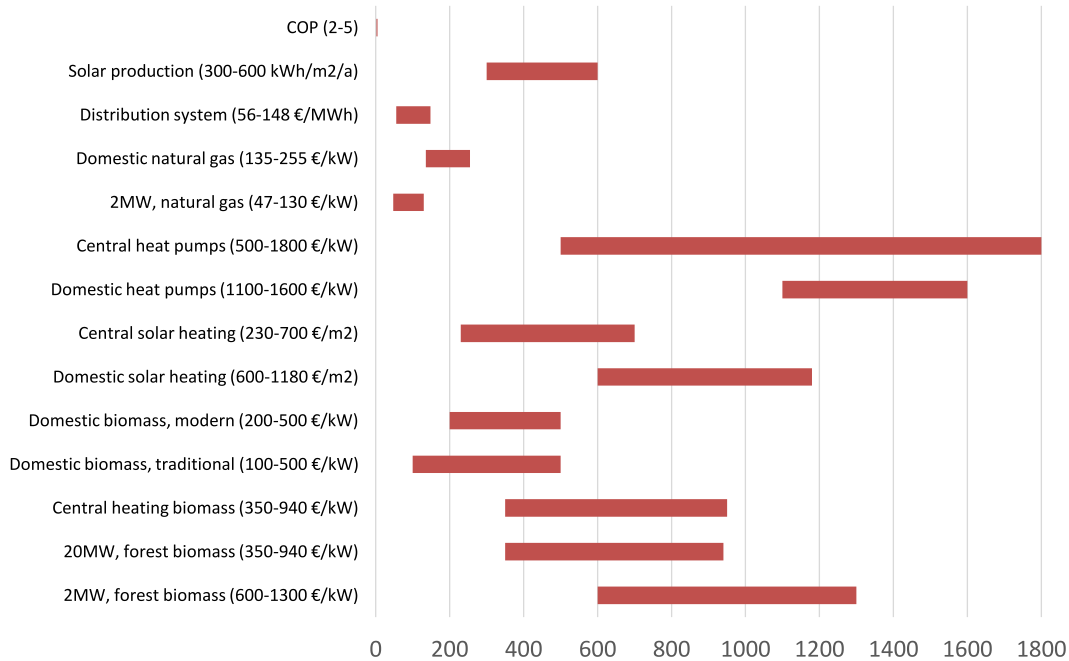

Fig. 4. The variation of investment costs and technical details based on [43,46].

assumptions are presented in Appendix A.

4.4. Portfolios

For the purpose of testing the proposed methodology for portfolio analyses, we used a simplified method to create the technology portfolios. We studied the heating technologies that could be attached to a district-heating network, so that a portfolio then illustrates a territorial energy system. The technologies selected for the analysis were a biomass-plant, central heat pumps and central solar heating solutions. We assumed that if the territory is interested in bioenergy production, it would build one larger bio-plant for the district heating network, and then produce the rest of the heating needed with the other technologies. No heat storages were included to simplify the analysis. Five different technology combinations were studied:

- Portfolio 1: Biomass-plant alone
- Portfolio 2: Biomass-plant + central heat pumps
- Portfolio 3: Biomass-plant + central solar heating
- Portfolio 4: Central heat pumps + central solar heating
- Portfolio 5: Biomass-plant + central heat pumps + central solar heating

We searched for solutions where the heat currently produced by natural gas is replaced by renewable energy. This is because we roughly estimated that households that are connected to the natural gas supply network exist in areas where it could be feasible to connect to the district heating system, i.e. they have a sufficiently high linear heat density. For a more detailed analysis, the heat demand should be evaluated based on high-resolution geospatial data [50]. We used the statistical data on natural gas consumption, which was available separately for heating and sanitary water [51]. To build the heat load curve, the monthly data on local temperatures for the region was used [52], and we assumed that heating was needed in months when the average temperature was <15 °C. Heating for sanitary water is needed all year round. This allowed us to roughly estimate the form of the heat load curve for the territory

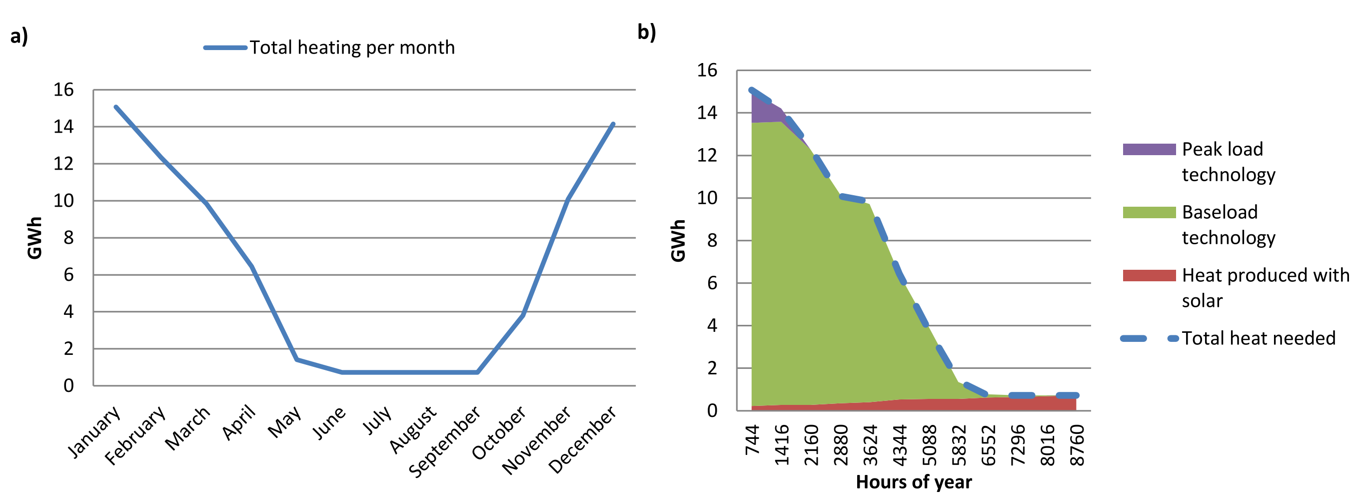

Fig. 5. a) The annual load curve illustrating the monthly heat consumption and b) an example of a sorted load curve used to define the shares of the production of the technologies.

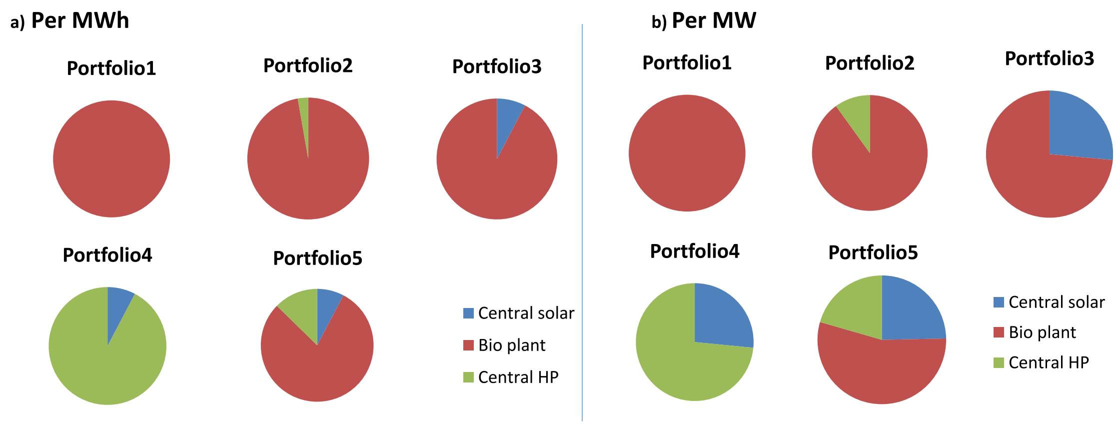

Fig. 6. Shares of technologies in portfolios defined a) by heat production (MWh) and b) by capacity (MW). HP = heat pump.

Table 5
Portfolio characteristics.

	Solar			Biomass-plant			Heat pumps		
				peak load time			peak load time		
	m^2	MW	GWh	average	MW	GWh	average	MW	GWh
Portfolio 1	0	0.0	0.00	3793	20	76			
Portfolio 2	0	0.0	0.00	3892	19	74	1002	2.1	2
Portfolio 3	9089	7.2	5.86	3510	20	70			
Portfolio 4	9089	7.2	5.86				3519	20.0	70
Portfolio 5	9089	7.2	5.86	3784	16	61	1608	6.0	10

(Fig. 5). To estimate the potential for solar heat production, we used the regional average solar radiation data for the years 2007–2016 from JRC [53], and made a cautious estimation of 40% for the thermal solar panels' efficiency.

To build a technology portfolio, we added the production technologies to the load curve. First, we assumed that if solar heating was included in the portfolio, the number of panels would correspond to the capacity that could produce the required heating for sanitary water during the summer months (any extra panels above this would produce waste heat during the summer, as no storage were included). The other technologies then produced the rest of the heat needed. We tested different shares of the other technologies, which were added to the load curve, unit by unit, first "baseload technology", then possible "peak load technology" (Fig. 5). By varying the share of the technologies, the economically optimal portfolio for each technology combination was found. This way, the final share of each technology in MWh and MW was defined, and the characteristics of the portfolios are illustrated in Fig. 6 and in Table 5.

5. Results and discussion

The results can be presented step-by-step, i.e. one metric after another before combining them. Each performance metric can be presented following the scheme presented below: comparing the performance of the technologies by regret analysis, assessing their robustness

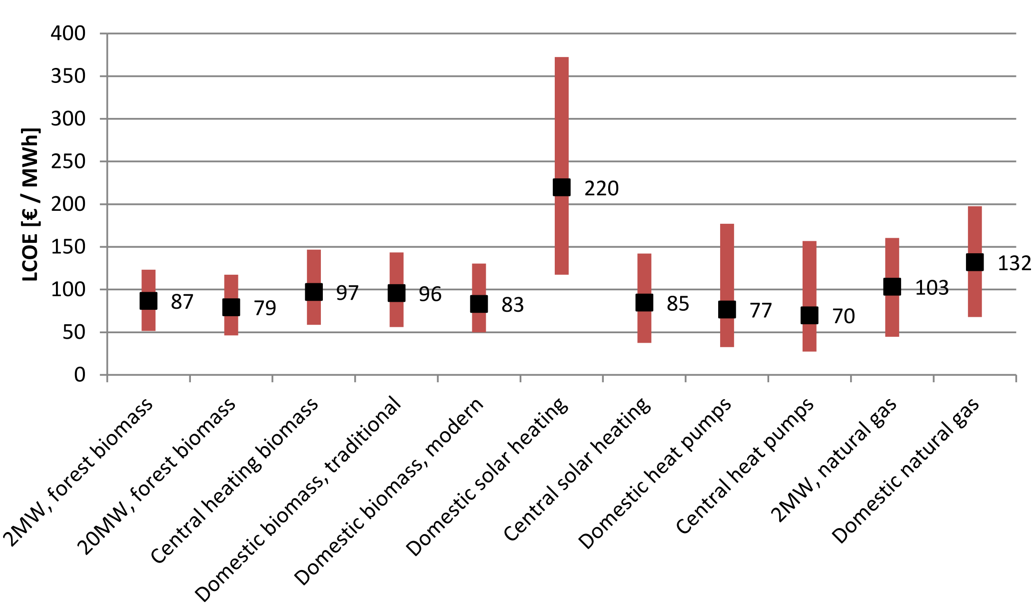

Fig. 7. The absolute LCOE average values and uncertainty ranges.

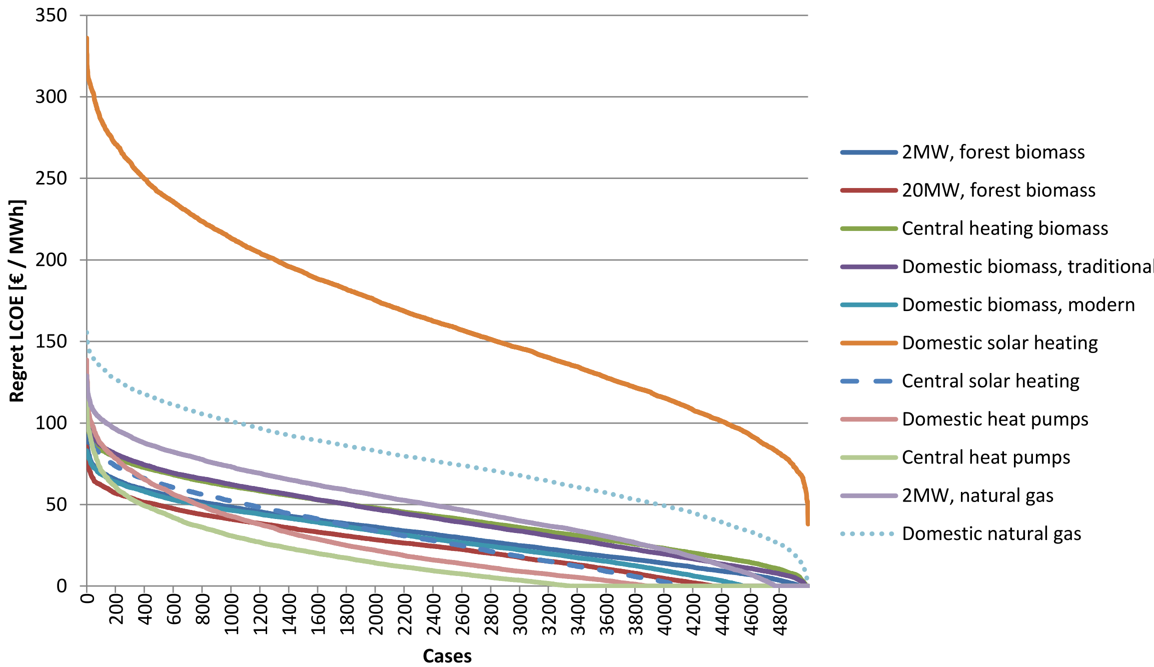

Fig. 8. Sorted regret for LCOE for 5 000 cases. The technology with the lowest regret in most of the cases is the most robust in various future conditions, in economic terms.

and vulnerabilities, then comparing the portfolios. Finally, the performance metrics can be combined, and weighting can be applied. This step-by-step approach is useful to help decision makers acknowledge, reinforce, or change their vision of the potential new territorial energy system. Here the economic performance is used as an example.

5.1. LCOE results and vulnerabilities for technologies

The absolute LCOE results for the technology comparison are shown in Fig. 7. The figure shows the variation due to the uncertainties applied and the average LCOE value.

The regret analysis according to Eq. (1) shows relative results comparing the technologies to each other. Economically speaking, and with the assumptions and uncertainty ranges applied in this study, the central and domestic heat pumps are the most interesting options, as they have the lowest regret in most of the cases. The sorted LCOE regret results (€/MWh) in Fig. 8 show that the central heat pumps perform the best in almost all of the 5000 futures simulated, and do so with most of the combinations of the varying calculation parameters. This illustrates that economically they are the most robust technologies when considering the future uncertainties. In addition, the large biomass-plant, modern domestic biomass and central solar heating perform well. None of the futures simulated made the domestic solar heating system successful due to its high investment cost. Additionally, the currently widely-used natural gas heating performed badly in all the futures.

We then continued to the PRIM analysis to determine the economic conditions which could make these best performing technologies vulnerable. We compared the central heat pumps to a 20 MW biomass-plant by calculating the regret results again between just these two options, and selected the worst 10% of the results as a threshold limit for the PRIM algorithm. To be able to recognise significant parameters, we fixed the peak load time of both technologies to be equal. The analysis provided us with parameters which had the most significant effect on the vulnerability of the technology, and the trade-off values with which these vulnerable futures could be experienced. The most significant parameters affecting the two technologies were the cost of electricity, the cost of biomass and the COP. For example, central heat pumps are

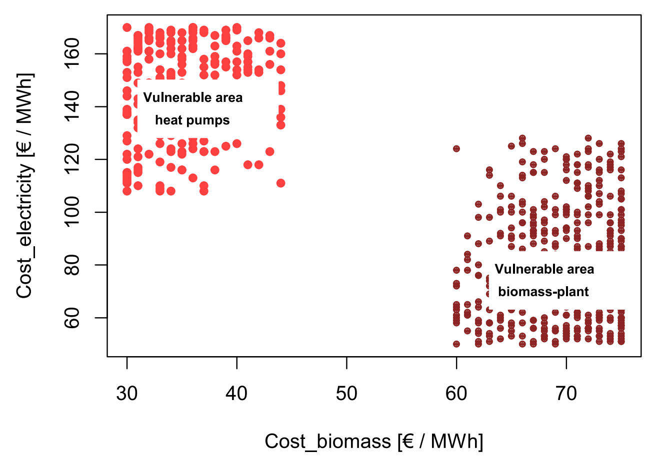

Fig. 9. Example economic conditions in which the best performing technologies are the most vulnerable.

vulnerable in conditions where the cost of electricity is >108 €/MWh, and the cost of biomass is <45 €/MWh. For the large biomass-plant these values are <29 €/MWh and >60 €/MWh, respectively. These vulnerable areas are illustrated in Fig. 9. The decision maker's role is then to judge (with experts), which of these future conditions can be considered the most probable in the investigated region. For example, if there are easily exploitable, low-cost biomass sources available in the region, but the future national electricity price is expected to rise significantly, the future conditions may be closer to those where the heat pumps are vulnerable and biomass-plant succeeds (or the other way round in opposite conditions).

5.2. LCOE results and vulnerabilities for portfolios

We conducted the regret analysis similarly for the portfolios. The sorted LCOE regret results in Fig. 10 show that Portfolios 1 and 4 have the lowest regret in most of the cases, thus being the most robust

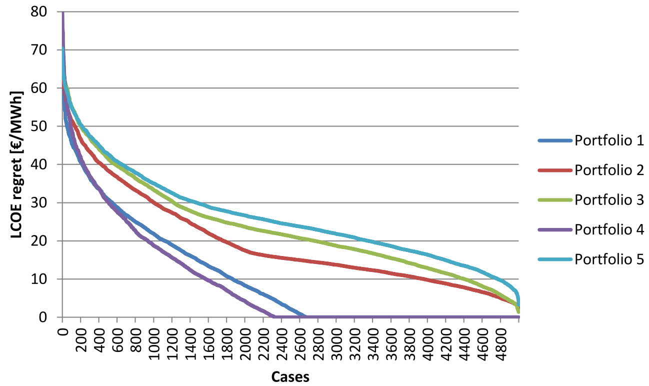

Fig. 10. Sorted regret for LCOE in 5 000 cases. The portfolio with the lowest regret in most of the cases is the most robust in economic terms, in various future conditions.

solutions in economic terms.

The PRIMS analysis was made for all the portfolios, again with the threshold limit of 10% of the worst LCOE results. The conditions making each portfolio vulnerable are given in Table 6. The cost of electricity and biomass and the COP of the heat pumps were the most significant parameters leading to vulnerability, the cost of biomass being the most significant parameter for all of the portfolios. At the same time, one can see that the other parameters, such as the investment costs, are less significant to the vulnerability of the results.

Fig. 11 illustrates the vulnerable areas for the two most promising portfolios, Portfolio 1 and Portfolio 4. Portfolio 1 relying only on biomass-plant is vulnerable when the price of electricity falls under 120€/MWh and the COP of the heat pumps is high (i.e. the heat pumps would perform efficiently). Portfolio 1 is vulnerable also, when the cost of biomass rises above 60€/MWh. Portfolio 4 relying on heat pumps becomes vulnerable when the price of biomass falls below 49 €/MWh, the COP is lower than 3, and the price of electricity rises above 100€/MWh. Again, it should then be judged, which conditions seem the most probable for the future in the region studied.

5.3. Total points with all performance metrics

When the total points from all performance metrics are calculated (equation (3)) and sorted for the technology comparison, we see the results in Fig. 12. The highest total points in most of the 5 000 cases are gained by the large biomass-plants. This means that this technology is the most robust in terms of all the performance metrics analysed, in various future conditions. Additionally, the smaller biomass-plants and heat pumps perform well.

Fig. 13 shows how the average total points are formed from the different performance metrics. This shows the differences between the technologies. Additionally, on average, the big biomass-plants and heat pump solutions performed the best. The worst results are for natural gas due to low points from GHG impacts, domestic solar heating due to low points from economic indicators, and for traditional biomass due low points from the health indicator ($PM_{10,2.5}$). It should be kept in mind, that the results are still dependent on the assumptions made concerning the uncertainty ranges, and more work is needed, for example, to define more reliably the job indicator.

Fig. 14 shows the corresponding results for the portfolios. Portfolio 4 has the highest total points in almost all 5 000 cases. This is because it performs the best for several indicators: particulate emissions, GHG emissions and often also the LCOE.

The PRIM analysis can be continued to study the vulnerabilities created by the various performance metrics, some individual metrics of interest, or different combinations of portfolios or technologies. It is up to the decision makers and analysts to decide which comparisons they consider the most useful for the studied situation.

Table 6
Vulnerable combinations of parameters for Portfolios. HP = heat pump.

	Investment bio €/kW	Investment HP €/kW	Investment solar €/kW	Solar production kWh/m^2/a	COP	Cost electricity €/MWh	Cost biomass €/MWh
Portfolio 1		<1378			>2.25	<119	>60
Portfolio 2					>2.55	<128	>67
Portfolio 3		<1380			>2.55	<137	>62
Portfolio 4					<3.05	>93	< 49
Portfolio 5					>2.25	<<120	>65

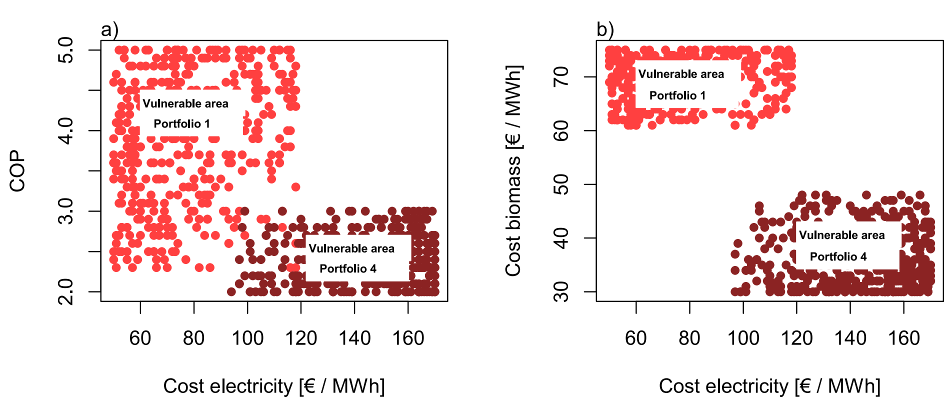

Fig. 11. Example conditions in which the best performing portfolios are the most vulnerable: a) trade-off with COP and electricity cost, b) trade-off with biomass and electricity cost.

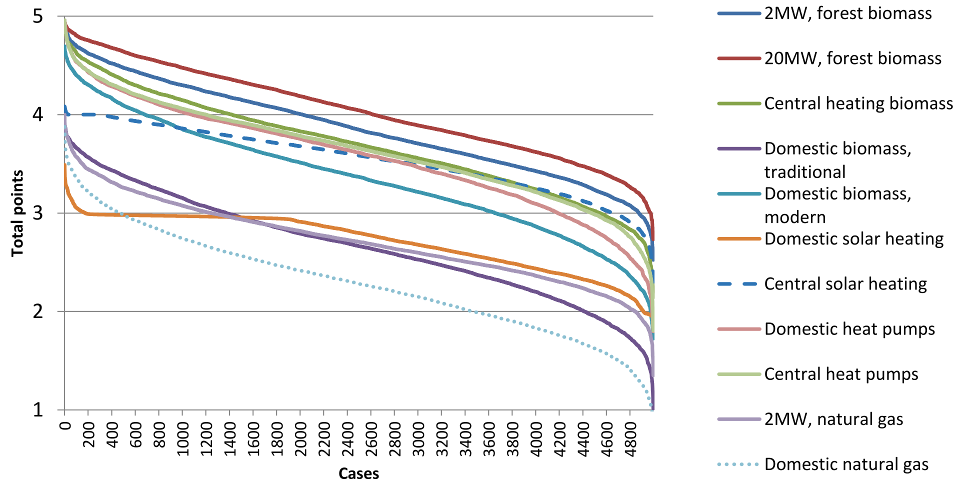

Fig. 12. Sorted total points in 5 000 cases for the technology comparison. The technology with the highest total points in most of the cases is the most robust in terms of all performance indicators.

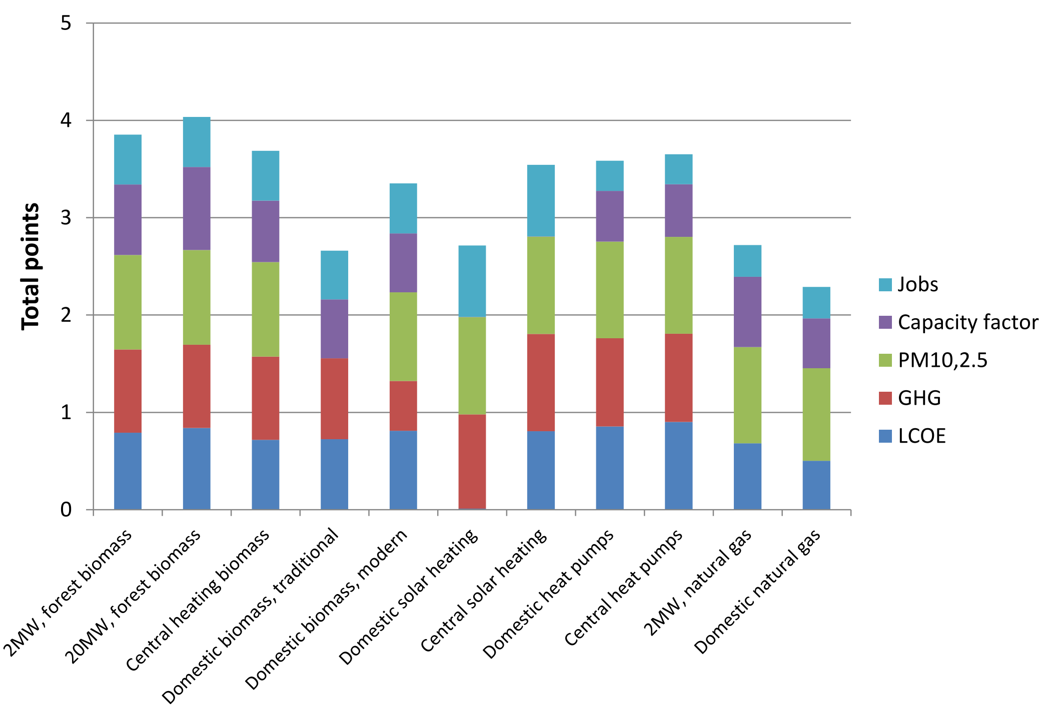

Fig. 13. Average total points for the technologies.

5.4. Preference scenarios and territorial weighting

If the decision makers wish to use weighting for the different performance metrics, one option is to use territorial features to do this, as described in Section 3.4. Fig. 15 illustrates an example of different weighting results for the total points, based on different preferences. If for example the region studied is poor and has a high unemployment rate, it may wish to emphasise the low costs of the technology and job creation, and a higher weight can be assigned to the LCOE and job indicator (e.g. a weight of 0.45 for economic and social indicators and 0.033 for other indicators). If the region wants to emphasise climate and health indicators, a higher weight is given to these indicators. A result with equal weight for all indicators is presented for comparison (weight of 0.2 for all indicators).

The example shows that the results can vary significantly between the weighting scenarios. For example, the domestic solar technology becomes significantly more interesting if a high weight is given only to climate and health impacts, instead of economic indicators.

6. Conclusions

This article presents a simple decision-making framework that can be used by territorial or other decision makers who need to consider multiple-criteria when deciding on future renewable energy investments under uncertainty. It searches for the technologies that are most robust in various future conditions, as well as for trade-offs between different parameters affecting the success of the renewable energy technologies. The proposed framework is flexible and it can be used with different simulation or optimisation models, as long as they allow running thousands of simulations. The case study on future heating solutions

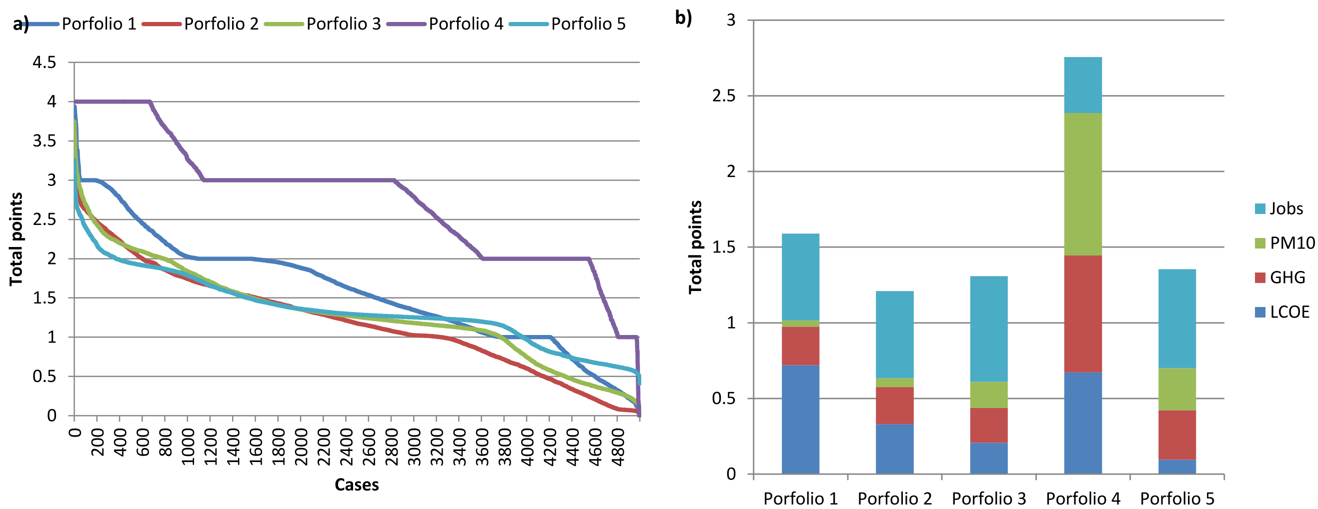

Fig. 14. Sorted (a) and average (b) total points for the portfolios.

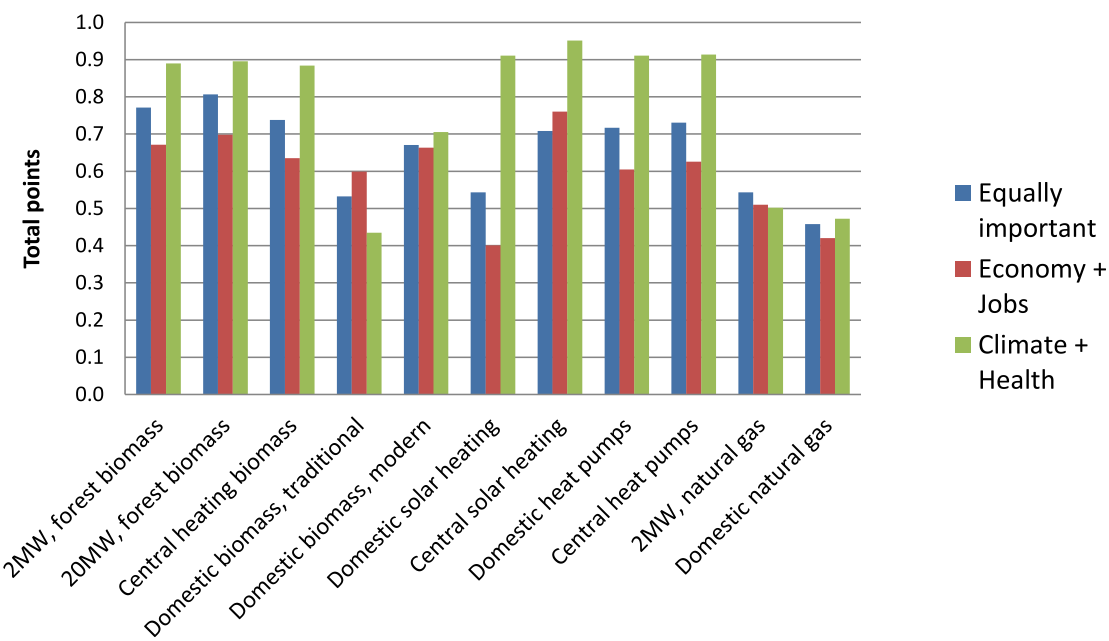

Fig. 15. Example illustration of applying weighting factors for the performance metrics.

gives guidance on how the analysis can be performed. It also shows that the currently widely-used natural gas heating performs badly in all simulated future conditions compared to renewable technologies. According to the study, heating solutions with heat pumps or central biomass plants are most robust in various future conditions.

The benefit of the method used is that it helps decision makers to recognise the most significant parameters creating vulnerabilities (or successful conditions) for the studied technologies. Thus, further efforts can be made to even better evaluate these particular parameters. The method shows the actual threshold values creating the vulnerable conditions for different technologies. Recognising and visualising these conditions and their trade-offs can help the decision makers to make concrete evaluations on the performance of the technologies, and to judge how well they would perform in future conditions foreseen in their region.

There are some limitations to the proposed decision-making framework to be tackled in future studies. For example, the uncertainty range was not applied for some of the parameters, e.g. here for operation and maintenance costs or for the discount rate. However, a change in these costs would affect the result. On the other hand, if too many uncertain parameters are included in the analysis, it can be difficult to find any clear vulnerable conditions with the PRIM analysis. Thus, a balanced approach is needed. In addition, even though the uncertainty range given for the parameters is wide, modifying it in one or another direction can affect the results. This can lead to subjectivity but also provides a more accurate vision of the uncertainties through iteration loops that can be made in co-operation with decision makers. Thus, further real-world test studies are needed.

The framework based on the robust decision-making method can offer interesting possibilities for creating data that can help territorial decision makers to make more comprehensively analysed decisions, with better understanding of various possible future conditions. In real life, it is not always possible to implement the most economically or environmentally optimal energy production system, as the future conditions are *per se* uncertain, or some other limitations such as economic resources, public opinion, or policy developments cannot be entirely modelled in particular in the long term (20 years or more). Thus, one option for the decision makers is to aim towards solutions which are the most robust in various future conditions. The framework proposed provides insight, among other methods, to make choices for the territorial energy transition.

CRediT authorship contribution statement

Kati Koponen: Conceptualization, Formal analysis, Writing - review & editing. **Elisabeth Le Net:** Funding acquisition, Conceptualization, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

See Table A1.

Table A1
Assumptions on emissions, capacity factor and jobs.

Identification	Technology	GHG emissions							PM 10 & 2.5 emissions					
		VARIED			FIXED				VARIED		FIXED			
		gCO_2/kWh	gCO_2/kWh						mg/kWh	mg/kWh				
		min	max	Source	min	max	Unit	Source	min	max	min	max	Unit	Source
Tech1	**2 MW, forest biomass**	21	64	RED2					4	40				ADEME, 2018
Tech2	**20 MW, forest biomass**	21	64	RED2					4	40				ADEME, 2018
Tech3	**Central heating biomass**	21	64	RED2					4	40				ADEME, 2018
Tech4	**Domestic biomass, traditional**	24	72	RED2					139	2390				ADEME, 2018
Tech5	**Domestic biomass, modern**	64	172	RED2					4	139				ADEME, 2018
Tech6	**Domestic solar heating**				137		$kgCO_2/m^2$	Ecoinvent 3.4			0	0.34	$kgCO_2/m^2$	Ecoinvent 3.4
Tech7	**Central solar heating**				137		$kgCO_2/m^2$	Ecoinvent 3.4			0	0.34	$kgCO_2/m^2$	Ecoinvent 3.4
Tech8	**Domestic heat pumps**	100		More&Lonza 2018	54		$kgCO_2eg$/kW	Ecoinvent 3.4	0.65	51	0	0.15	kg/kW	Ecoinvent 3.4
Tech9	**Central heat pumps**	100		More&Lonza 2018	54		$kgCO_2eg$/kW	Ecoinvent 3.4	0.65	51	0	0.15	kg/kW	Ecoinvent 3.4
Tech10	**2 MW, natural gas**	221	243	Statistics Finland					0.02	19				Ecoinvent 3.4
Tech11	**Domestic natural gas**	221	243	Statistics Finland					0.04	78				Ecoinvent 3.4

Identification	Technology	Capacity factor			Jobs		
					jobs/GWh		
		min	max	Source	min	max	Source
Tech1	**2MW, forest biomass**	0,46	0,86	S2Biom, ADEME 2016	0.18	2.40	ADEME 2017, Klein & Whalley 2015
Tech2	**20MW, forest biomass**	0,51	0,97	S2Biom, ADEME 2016	0.18	2.40	ADEME 2017, Klein & Whalley 2015
Tech3	**Central heating biomass**	0,34	0,86	S2Biom, ADEME 2016	0.18	2.40	ADEME 2017, Klein & Whalley 2015
Tech4	**Domestic biomass, traditional**	0,26	0,91	S2Biom, ADEME 2016	0.16	2.40	ADEME 2017, Klein & Whalley 2015
Tech5	**Domestic biomass, modern**	0,26	0,91	S2Biom, ADEME 2016	0.19	2.40	ADEME 2017, Klein & Whalley 2015
Tech6	**Domestic solar heating**	0,18	0,28	Klein & Whalley 2015	0.86	2.43	Klein & Whalley 2015
Tech7	**Central solar heating**	0,18	0,28	Klein & Whalley 2015	0.86	2.43	Klein & Whalley 2015
Tech8	**Domestic heat pumps**	0,17	0,90	ADEME 2016	0.37	1.60	Klein & Whalley 2015
Tech9	**Central heat pumps**	0,21	0,90	ADEME 2016	0.37	1.60	Klein & Whalley 2015
Tech10	**2MW, natural gas**	0,46	0,86	ADEME 2016	0.24	1.76	Klein & Whalley 2015
Tech11	**Domestic natural gas**	0,26	0,91	ADEME 2016	0.24	1.76	Klein & Whalley 2015

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